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Quantifying forest carbon stocks by integrating satellite images and forest inventory data

Quantifizierung der Kohlenstoffvorräte in Wäldern durch die Integration von Satellitenbildern und Waldinventurdaten

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Schlüsselbegriffe: *oberirdische Biomasse, Fernerkundung, Sentinel-2A-Daten, Vegetations-Indizes*

Abstract

Reliable biomass and carbon stock estimation are central to obtain reference levels for quantifying carbon emissions. Forest inventory data combined with remote sensing data provides opportunities to map and monitor forest areas at various spatio-temporal scales. The current research is a pilot study focussed on the biomass and carbon estimation and mapping of subtropical scrub forests of Khanpur range, Haripur Forest Division, Pakistan considering 20 inventory plots using Sentinel-2A and Landsat-8 data. Six forest areas (Garamthun, Chhoi, Moharagutta, Sanaba, Dobandi and Saradana) were considered covering a total area of 697.3 ha. Average biomass of

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the assessed plots was 104.6 t/ha and mean carbon stock was 49.7 t/ha. Garamthun forest had the highest values for both biomass (187.30 t/ha) and carbon (87.98 t/ha) followed by Choi with 148.22 t/ha of biomass and 69.6 t/ha carbon respectively. The total estimated carbon stock for these six forest types was 43570.9 t. The biomass was then correlated with spectral indices computed from Sentinel 2 image (NDVI, SAVI, DVI, PVI and MSAVI). NDVI performed significantly well among five other indices with the values of R2 of 0.81 followed by 0.7 and 0.58 for SAVI and DVI respectively. PVI and MSAVI responded poorly to biomass as compared to the other indices with the value of R2 of 0.20 and 0.11 respectively. Spatial distribution of biomass was mapped using NDVI, which was selected as the best model based on the values of R2. Further, Landsat-8 was also used and the similar five indices were derived for Landsat-8 imagery. Finally, both the indices derived from Sentinel-2A and Landsat-8 were compared. Scrub forests of Khanpur showed the largest potential for carbon sequestration and storage. It is suggested that this method is not only used for the Haripur district in Khyber Pakhtunkhwa, whose forest division extends merely over the area of 42491 ha; rather it should be applied to the entire forest area of Pakistan for national forest inventory. The research concluded that Sentinel 2 has the best combination of spectral capabilities and broad spectrum of applicability.

Zusammenfassung

Zuverlässige Schätzungen von Biomasse und Kohlenstoff sind sehr wichtig für die Quantifizierung der Treibhausgasemissionen. Waldinventurdaten in Kombination mit Fernerkundungsdaten ermöglichen das großflächige Monitoring von Waldgebieten auf unterschiedlichen räumlicher und zeitlicher Auflösung. Diese Pilotstudie konzentrierte sich auf die Biomasse- und Kohlenstoffschätzung und deren Kartierung für die subtropischen Buschwälder in der Khanpur Region in Pakistan (Forstabteilung Haripur) mittels 20 Probeflächen und Sentinel-2A und Landsat-8 Daten. Mit sechs Waldgebieten (Garamthun, Chhoi, Moharagutta, Sanaba, Dobandi und Saradana) wurde insgesamt eine Fläche von 697.3 ha untersucht. Durchschnittliche Biomasse der untersuchten Probeflächen war 104.6 t/ha und der Kohlenstoffvorrat war 49.7 t/ha. Garamthun weist die höchsten Werte auf, sowohl für Biomasse (187.30 t/ha) als auch für Kohlenstoff (87.98 t/ha), gefolgt von Choi mit 148.22 t/ha Biomasse und 69.6 t/ha Kohlenstoff. Der Kohlenstoffvorrat für alle 6 untersuchten Wälder wurde auf 43570.9 t geschätzt. Die Biomasse wurde dann korreliert mit spektralen Vegetationsindizes errechnet aus Sentinel-2A Daten (NDVI, SAVI, DVI, PVI und MSAVI). NDVI liefert die besten Ergebnisse mit einem Bestimmtheitsmaß (R2) von 0.81, gefolgt von R2 0.7 und 0.58 für SAVI und DVI. PVI und MSAVI haben am schlechtesten abgeschnitten im Vergleich zu den anderen Indizes mit R2 von 0.20 und 0.11. Die räumliche Verteilung von Biomasse und Kohlenstoff wurde mittels NDVI abgebildet. Außerdem, wurden aus Landsat-8 ebenfalls die 5 Vegetationsindizes berechnet und mit den Ergebnissen von Sentinel-2A verglichen. Die Buschwälder von Khanpur weisen großes Potenzi-

al zur Kohlenstoffbindung und -speicherung auf. Es wird empfohlen diese Methode nicht nur für die Haripur Region im Khyber Pakhtunkhwa zu verwenden, deren Waldfläche bloß 42491 ha beträgt, sondern für die gesamte Waldfläche von Pakistan als Waldinventur zu verwenden. Unsere Untersuchungen kommen zu dem Schluss, dass Sentinel-2A-Daten am besten dafür geeignet sind durch deren hohe Genauigkeit und breites Anwendungsspektrum.

1. Introduction

Deforestation and forest degradation contributes to increasing carbon dioxide concentration in the atmosphere. CO_2 acts as a major greenhouse gas. Globally, forest area has decreased from 31.6% in 1990 to 30.6% in 2015 (FAO, 2015) particularly due to anthropogenic activities thereby contributing to global climate change. Alternatively, afforestation and forest restoration activities reduce GHG emissions from forest ecosystem. It is estimated that with decline in deforestation rate between 2001 and 2015, the carbon emissions from forests have also been decreased by more than 25 % globally (FAO, 2015). Reducing Emissions from Deforestation and Forest Degradation (REDD+) is an initiative to reduce the deforestation, forest degradation and carbon emissions from forest ecosystems in developing countries. REDD+ implementation requires appropriate estimates of forest biomass and quantifying carbon stocks.

Field measurements provide to most reliable estimates of forest carbon (Tomppo et al., 2010). On the other hand, its applicability to larger areas is restricted by large expenses, time and labor constraints. Remote sensing is considered to be a consistent and dependable solution to these challenges, as it provides large area coverage in both spatial and temporal domains (Shi, 2010; Du et al., 2014). These methods not only accelerate data collection process but also exactly monitor and map various forest characteristics at local and regional scale. (Lu, 2006; Rabindranath et al., 2008). By linking remote sensing with forest inventory data, reliable large scale maps of forest characteristics can be produced (Moreno et al., 2017). Although, remote sensing provides sound biomass estimates; but few errors like geometric, radiometric and atmospheric distortions may lead to overestimation or underestimation of forest features while dealing with different resolutions (Kindermann et al., 2008; Zheng et al., 2008). However, careful validation is needed to prove the reliability and accuracy. Options involve cross validation, validation with an independent dataset (not used for model development) or evaluation with other datasets (Mayaux et al., 2006; Friedl et al., 2010; Simard et al., 2011; DiMiceli et al., 2011; Galidaki et al., 2017). United Nations Framework Convention on Climate Change (UNFCCC) has recommended the methodological guidance for REDD+ activities to use remote sensing and ground-based carbon measurements for carbon biomass estimation, GHG emissions and forest area changes due to deforestation and forest degradation (Decision 4/CP.15, UNFCCC 2014).

Remote sensing data such as Landsat are widely for forest mapping, monitoring and biomass assessment (Hansen et al, 2013; Gasparri et al, 2010), its free data availability, spatial coverage and temporal capabilities make Landsat one of the most extensive and boundless used data for vegetation analysis (Gizachew et al, 2013). The biomass estimation through Landsat is commonly through establishing relationships between above ground biomass and different vegetation indices (Lu 2005; Nelson et al, 2000; Foody et al, 2003). Sentinel 2 is the state of the art sensor providing products with wide spatial coverage, high spatial and temporal resolution (Fletcher, 2012; Drusch et al., 2012) for many of its applications in forestry sector; such as forest classification (Immitzer et al., 2016), biomass estimation and mapping (Chang and Hoshany, 2016), biophysical variables (Frampton et al., 2013; Sakowska et al., 2016; Korhonen et al., 2017), forest burn area management (Verhegghen et al., 2016) and species mapping (Ng et al., 2017). The Sentinel 2 product provides high resolution with four bands at 10 meters resolution; Blue-Band 2, Green-Band 3, Red-Band 4 and NIR-Band 8) and 20 meters resolution; NIR-Band 8A (Fletcher, 2012; Drusch et al.,2012; Adnan, 2017). Band resolutions, band widths and central wavelength information of Sentinel-2A are summarized in Table 1.These bands cover major portion of vegetation absorption and reflectance behavior. Other bands such as Band 5,6 and 7 provide information like Red-edge properties to analyze vegetation dynamics (Chen et al., 2007; Cao et al., 2016) and Band 12 and 13 provide information about canopy water content (Ceccato et al., 2001; Hunt and Qu, 2012;). Moreover, these bands are also useful to develop strong relationship with forest attributes. Vegetation and forest attributes can be smoothly assessed by computing relationship between spectral indices and ground based measurements (Barati et al., 2011). Several studies applied Sentinel 2 spectral indices on vegetation and obtained significant results with acceptable accuracy (Delegido et al., 2011; Atzberger et al., 2012; Frampton et al., 2013; Vuolo et al., 2016; Majasalmi & Rautiainen., 2016). Presently, compared to other sensors such as LANDSAT, ASTER, SPOT and MODIS which have been used extensively for biomass estimation, Sentinel 2 sensor is very much less explored for its forestry applications specifically for biomass estimation.

This study will discover Sentinel 2 sensor product and evaluate its potential to estimate biomass by deriving various indices and spectral properties. The objectives of the study include; (1) estimate biomass and carbon storage in six selected forest areas (2) evaluation of several indices and to extrapolate the most suitable index for study area (3) compare various Sentinel-2A indices with Landsat-8 derived indices.

2. Materials and Methods

2.1 The study area

The Khanpur forest range falls under the jurisdiction of Haripur forest division of district Haripur as shown in Fig.1. Haripur is administrative unit and located in southern part of Khyber Puktunkhwa province of Pakistan. Geographically, Haripur is situated at latitude 33° 44' to 34° 22' and longitude 72° 35' to 73° 15'. The total area of district Haripur is 1725 km² with 466 inhabitants per km². Agriculture is main livelihood of rural population. The district has 77370 acres arable area. The total forest area of district Haripur is 42491 hectares which forms 23.1% of the total area (Working Plan, 2008). For better management, Haripur forest division is further subdivided in five forest ranges namely; Haripur mian, Makhnial, Ghazi , Satora and Khanpur range. Generally the tract is mountainous. The elevation varies from 625 m to 2031 m. The parallel mountainous ridges running from north east to south west with intervening nullahs constitute Satura, Makhnial and Khanpur ranges. Haripur range is mostly plain. Ghazi Range is partly is plain and partly mountainous. Due to mountainous nature of the tract, climate varies from place to place depending upon the altitude. Due to low elevation Khanpur, Haripur and Ghazi have hot summers and very cold winters. Makhnial and Satura ranges have pleasant summers and less severe winters. Snowfall and winter rains are received from December to March. Major portion of the annual precipitation is received in monsoon season that is the seasonal shift in the direction of wind followed by heavy precipitation. In Pakistan, normal duration of monsoon rainfall is from June to October. The district Haripur has two major forest types i.e. Sub-tropical Chir Pine and Sub-tropical scrub forests. This research study focused six reserved forest areas of only Khanpur scrub range which include Chhoi, Garamthun, Mohara-gutta, Sanaba, Dobandi and Saradana. The total area of Khnapur range is 1588.36 ha, out of which 158.24 ha is blank and the total area of above-mentioned six sampled forest areas is 697.3 ha (Working of Haripur reserved forests, 2008).

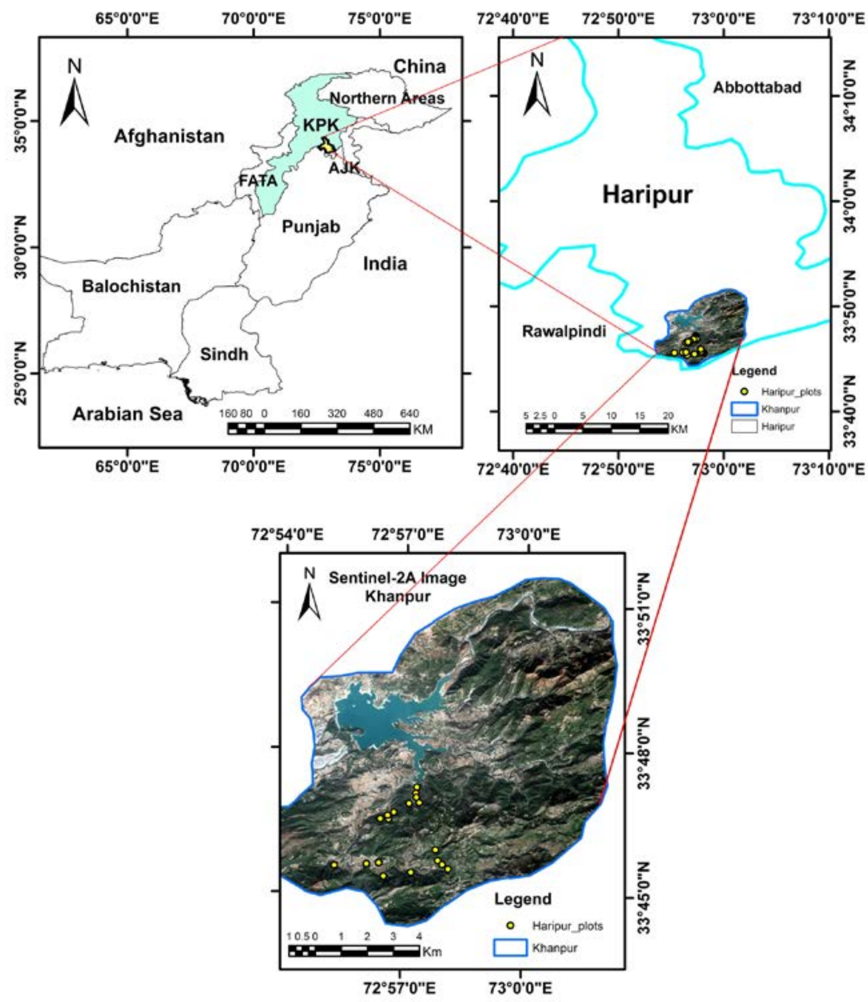

Figure 1: Overview and location of study area

Abbildung 1: Übersicht und Lage des Untersuchungsgebietes

2.2 Forest Inventory

A total of 20 circular sample plots of 0.1 ha area were randomly laid out in the forest and all the trees inside the circle were enumerated as shown in Figure 2. Locations of all plots were recorded using Global Positioning System (GPS) receiver. Sampling and measurements were conducted with great care as accuracy of biomass depends upon these variables (Chave et al., 2004; Samalca, 2007; Molto et al., 2013). Diameter at breast height (DBH) and height of all trees in a sample plot were measured for above ground biomass estimation. Six species encountered during inventory which include Acacia nilotica, Acacia modesta, Olea ferrugineae, Zizyphus jujuba and Ficus palmata, whereas Dodonaea viscosa is the main shrub species in the area. All the necessary materials that were used for data collection and further processing are given in Table 1.

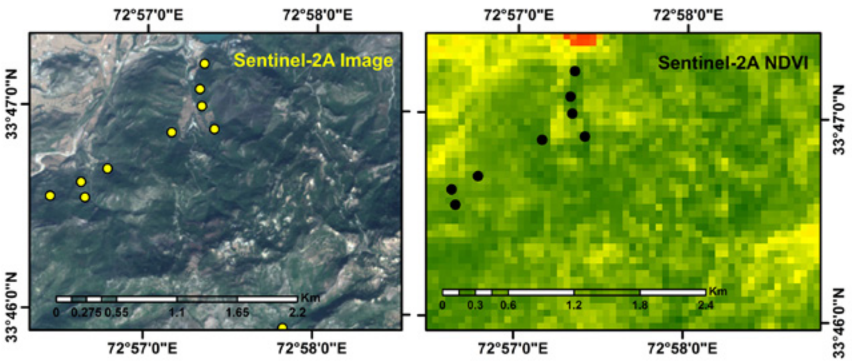

Figure 2: Sentinel-2A imagery and inventory plots

Abbildung 2: Sentinel 2A-Bild und Inventurplots

Table 1: Sentinel 2 Bands Description (ESA, 2010)

Tabelle 1: Beschreibung der Sentinel 2-Spektralbänder (ESA, 2010)

Spectral band	B1	B2	B3	B4	B5	B6	B7	B8	B8a	B9	B10	B11	B12
Spatial resolution (m)	60	10	10	10	20	20	20	10	20	60	60	20	20
Central wavelength (nm)	443	490	560	665	705	740	783	842	865	945	1375	1610	2190
Bandwidth (nm)	20	65	35	30	15	15	20	115	20	20	30	90	180

For the carbon inventory all the trees with a DBH of ≥ 5 cm were measured except that of Dodonaea viscosa whose basal diameter was found to be less than < 5 cm so all plants of that species were measured at the base. Biomass of Dodonaea viscosa was determined using the following allometric equation (Litton, 2008):

$$AGB = 0.13\, D^{2.55} \qquad (1)$$

where
AGB is the aboveground biomass in g and D is the diameter at base in mm.

The heights of trees were measured with Haga Altimeter, diameter at breast height (1.37 m) with Diameter tape, radius of the circular plot with measuring tape and angles (degrees) with Suunto compass. Odd shaped trees i.e. buttressed or forked trees were also measured keeping in mind all the necessary points. Species volume was calculated using the local volume tables prepared by Pakistan Forest Institute, Peshawar. The volume was calculated from diameter, height classes and form factor mentioned in volume table by using the formula (Equation 2). Volume for all species was estimated by assuming conical shape stem.

$$Vol = BA \times Ht \times FF \qquad (2)$$

where
Vol is the volume in m^3, BA is the basal area in m^2 and FF is form factor.

As there were six species under this research study, separate volume table for each one was used except *Dodonaea viscosa* whose biomass was directly calculated owing to the fact that diameter at base was too small therefore biomass was calculated directly using the equation (Litton, 2008). Volume of all other species was calculated by comparing diameter classes against their volumes mentioned in available literature i.e. "local metric volume tables prepared for Farmlands of Charsadda." The volume of each plot was calculated by adding the volume of entire individual trees in that sample plot. The average volume per plot for every specie was also determined by adding up volume of all trees in that sample plot and dividing it with the total number of sample trees in that plot. Thus the volume of each sample plot was converted into volume/ha by multiplying the volume of each plot with 10, because area of each plot was 0.1 ha. Furthermore, in order to obtain the total volume of the Khanpur forests; volume/ha was multiplied with total number of ha in that forest. The above ground biomass was calculated by multiplying volume with basic wood density and biomass expansion factor (Schoene., 2002), to expand estimates to other non-merchantable parts of the tree (Milne et al., 1998; Fukuda et al., 2003; Penman et al., 2003). The formula is given below:

$$Biomass = V \times BWD \times BEF \qquad (3)$$

where
V is the timber volume in m^3 and

BWD is the basic wood density in kg/m^3;

BEF is the biomass expansion factor which is equal to 1.4.

For this research study, separate basic wood density values for each species were applied which are given in Table 3. It is generally considered that about half of the dry biomass consists of carbon (Roy et al., 2001, Malhi et al., 2004). Thus the dry biomass can be converted to carbon stock by multiplying it with 0.47 (Paustian et al., 2006). Below ground biomass (BGB) was estimated by multiplying the above ground biomass with 0.26 as per IPCC guidelines (Ravindranath and Owtwald, 2008). IPCC is an acronym for Intergovernmental Panel on Climate Change. It provides the methods for the estimation of changes in carbon stocks and greenhouse gas emissions along with the changes in biomass content on forest lands. The dry biomass (above ground and below ground) can be converted to carbon stock by multiplying it with 0.47 (Paustian et al., 2006) to get Above Ground Carbon stocks (AGC) and Below Ground Carbon stocks (BGC) as it is generally considered that about half of the dry biomass consists of carbon (Roy et al., 2001, Malhi et al., 2004). The carbon stock was then converted into CO_2 equivalent by multiplying it with 3.66 (Pearson et al., 2007) which is the ratio of carbon atom in the molecular weight of CO_2. Thus, the total amount of CO_2 sequestered was determined. The quantity of carbon stocks facilitates the determination of total number of carbon credits as each carbon credit is equal to one metric ton of carbon dioxide. These carbon credits calculations are important part in national Greenhouse gases (GHGs) mitigation. Moreover, after assuming the price of a carbon credit, one can also estimate the revenue to be generated from these carbon credits. In this study, the price of carbon has been assumed to be 30 US$ per ton of carbon (Nordhaus, 2008).

2.2.1 Sentinel-2 and Landsat 8 Images Processing

The present study used Sentinel-2 imagery for biomass estimation because Sentinel-2 data product has overcome limitation of resolution (Gascon and Berger, 2007) that was previously provided by other open source sensors. The imagery was downloaded from Copernicus Sentinel Scientific Data Hub (https://scihub.copernicus.eu/) for Khanpur range (Dated October 28, 2016). The Sentinel product was named as S2_MSI_Level-1C with processing Level-1C. Product bands ranged from 443 to 2190 nm with Band 2, 3, 4 and 8 in 10 m, Band 5, 6, 7, 8A, 11 and 12 in 20 m and Band 1, 9 and 10 in 60 m. The product area was approximately 100 km² which covered not only the entire Haripur but also extended to other neighbor districts such as Rawalpindi, Abbottabad, Mansehra and Swabi. The primary step was image pre-processing before its use for biomass estimation purpose (Roy et al., 2016). The purpose was to avoid effects of atmospheric scattering or cloud cover shadows, to aid visual interpretation and to extract plenty of information from remotely sensed imagery. Pre-processing includes radiometric, geometric and terrain correction respectively. Sentinel-2 images were preprocessed in SNAP Tool Box (Egbers, 2016; Martins et al., 2017). Sen2Cor-2.3.1 is a plugin in SNAP tool box for atmospheric correction of the Sentinel-2 images. Level 1C product can be converted into atmospherically corrected Level 2A product (Wilm, 2016). The processing of Level 1C product includes cloud detection, scene classification, Aerosol optical thickness and water vapor content, all these were done by Sen2Cor 2.3.1 processor to obtain bottom of atmosphere conversion (BoA) (Knorn et al., 2015; Louis et al., 2016; Martins et al., 2017). Sub-setting of image was done for the area of interest where forest inventory was conducted. Furthermore, resampling of 20 m bands was done and inventory plots were overlaid (Figure 2). According to Chrysafis et al. 2017, different vegetation indices from Sentinel-2A product were computed using SNAP Tool box to assess biomass. Various indices, their formulae and Sentinel-2 bands were shown in Table 2. AGB (Above ground biomass) shape file created via ArcGIS 10.3 was overlaid on corresponding vegetation indices of both the acquired images. The values of masked pixels by inventory plots were extracted for all the indices. Similarly, The Landsat-8 Product was downloaded from USGS Earth Explorer (https://earthexplorer.usgs.gov/) for Khanpur range. The preprocessing was the first step; the ENVI 5.3 was used for preprocessing of the Landsat-8 imagery, including Radiometric Calibration, Reflectance Correction and Dark Subtraction. Further, the rectified image was used to compute various indices such NDVI, SAVI, MSAVI, PVI and DVI, as previously computed for Sentinel-2A imagery. The AGB point data was imported on these indices and the values of masked pixels was extracted.

Table 2: Vegetation Indices for Sentinel-2A and Landsat-8 Product

Tabelle 2: Vegetationsindizes für Sentinel-2A und Landsat-8 Daten

Indices	Formula	Sentinel-2A	Landsat-8	Original Author
Normalized Vegetation Index (NDVI)	(NIR- Red) ÷ (NIR + Red)	(B8A- B4) ÷ (B8A + B4)	(B5- B4) ÷ (B5 + B4)	Rouse et al. 1973
Soil Adjusted Vegetation Index (SAVI)	((NIR - R) ÷ (NIR + R + L)) × (1 + L)	((B8A - B4) ÷ (B8A + B4 + 0.5)) × (1+0.5)	((B5 - B4) ÷ (B5A + B4 + 0.5)) × (1+0.5)	Qi et al. 1994
Difference Vegetation Index (DVI)	NIR - R	(B8A - B4)	(B5 - B4)	Jordan 1969
Modified Soil Adjusted Vegetation Index (MSAVI)	1÷2 [2NIR+1-sqrt((2NIR+1)-8(NIR-R))	1÷2 [2B8A+1-sqrt((2B8A+1)-8(B8A-B4))	1÷2 [2B5+1-sqrt((2B5+1)-8(B5-B4))	Qi et al. 1994
Perpendicular Vegetation Index (PVI)	(a × NIR –R + b) ÷ sqrt(a^2 + 1)	(a × B8A - B4 + b) ÷ sqrt(a^2 +1)	(a × B5 - B4 + b) ÷ sqrt(a^2 +1)	Perry & Lutenschlager (1984)

Table 3: Basic Wood Density of important species in the study region (Sheikh, 1993)

Tabelle 3: Holzdichte wichtiger Baumarten des Untersuchungsgebietes (Sheikh, 1993)

S.No	Name of the Species	Wood Density (t/m^3)
01	*Acacia nilotica* (Babul/Kikar)	0.75
02	*Acacia modesta* (Phulai)	0.96
03	*Olea ferruginaea* (Kahu)	1.12
04	*Zizyphus jujuba* (Ber)	0.93
05	*Ficus Palmata* (Fig)	0.40

2.3. Statistical Analysis

Scatter plots were generated to analyze the relationship between biomass and individual indices. Correlation and regression analysis were performed between biomass and spectral indices. Different models were established (linear, polynomial, power, logarithmic and exponential). Coefficient of determination (R2) was calculated for each model. As a result, model fulfilling the condition of highest value of R2, was selected for effective biomass estimation and generation of biomass map as well.

3. Results and Discussion

3.1 Stem Number

The stocking of the six scrub forests have been summarized in Table 6. The total forest area in these six villages is 697.3 ha consisting of total 759783 trees. The respective forest areas of the sampling areas were obtained from Working Plan of Haripur (2008). Data shows that density was highest in Garamthun with 1350 trees per ha followed by Dobandi with 880 trees per ha (Table.6). The Mohara Gutta with 650 trees per ha was found to be least stocked forest area.

3.2 Volume (m^3) (Plot level and Forest-wise)

The total trees per ha in the study area indicating that the forests were well stocked. As per Table 4, Acacia modesta is the species with the highest volume of 33.19 m^3 per ha followed by Olea ferruginaea whose volume equals to 22.37 m^3 per ha. The volume of Acacia nilotica, Zizyphus jujuba and Ficus palmata were calculated as 0.99, 0.73 and 0.38 m^3 per ha respectively. The total volume in the study area was estimated as 51045 m^3 for five species except Dodonaea viscosa because local volume table was not available. The volume for each forest is summarized in Table 6. It was found that forest of Garamthun contains highest volume of 102.5 m^3/ha followed by Chhoi, Mohara-gutta, Sanaba and Dobandi forests with 80.2 m^3/ha, 31.2 m^3/ha, 30.5 m^3/ha and 29.1 m^3/ha respectively. Whereas, Saradana forest had lowest volume with more than 20.7 m^3/ha. (Nizami, 2012) studied different species of subtropical broadleaved evergreen forests (scrub) had major species Acacia modesta and Olea ferruginaea and reported volume per hectare (m^3/ha) at two different study sites (Kherimurat and Sohawa) with total volume (m^3/ha) of 12.86 and 11.40 respectively. Regarding composition of tree species in study area, Acacia modesta is ranked highest with 57 % followed by Olea ferrugineae with 39 % whereas Acacia nilotica, Zizyphus jujuba and Ficus palmata were last in the ranking.

Table 4: Species-wise volume for all species except Dodonea viscosa but its base diameter was directly converted to biomass by using allometric equation

Tabelle 4: Baumvolumen aller Baumarten (außer für *Dodonea viscosa* deren Durchmesser direkt mittels allometrische Gleichung in Biomasse umgerechnet wurde)

S.No	Name of Species	DBH Range (cm)	Height Range (m)	No of Sample Plots	Average Volume (m^3) per ha
01	*Acacia modesta*	6 to 28	4 to 11	20	33.19
02	*Olea ferrugineae*	8 to 26	3 to 13	20	22.37
03	*Acacia nilotica*	4 to 12	3 to 8	20	0.99
04	*Zizyphus jujuba*	6 to 14	4 to 9	20	0.73
05	*Ficus palmata*	8 to 12	5 to 7	20	0.38
	Total				**57.66**

3.3 Biomass and Carbon Stocks (Plot & Forest level)

The highest AGB and BGB was found to be 148.65 and 38.65 t/ha respectively whereas mean biomass (including both AGB and BGB) was found to be 104.6 t/ha as shown in Table 5. The highest estimated carbon stocks were 69.84 and 18.14 t/ha for AGC and ABC respectively whereas highest carbon stock (including both AGC and ABC) was determined as 87.98 t/ha. Carbon stock of Garamthun forest were the highest 32931.9 t carbon followed by Choi with 4987.6 t of carbon (Table 6). Whereas, the values of biomass and carbon were lowest for Saradana forest with 2567 t of biomass and 1206.4 t of total carbon stocks respectively. The total carbon stocks for these six forests types were 43570.9 t. Nizami, (2012) reported mean AGB (t/ha) for two dominant species (Acacia modesta and Olea ferrugineae) in two study sites (Kherimurat and Sohawa) as 50.93 and 40.43 t/ha respectively. In the past study reported by Nizami (2012) mean carbon stocks were estimated as 25.54 and 20.23 t/ha at two sites (Kherimurat and Sohawa) respectively.

Table 5: Biomass and carbon stocks of the sample plots

Tabelle 5: Biomasse und Kohlenstoffvorrat der Probeflächen

Plot No	**AGB (t/ha)**	**AGC (t/ha)**	**BGB (t/ha)**	**BGC (t/ha)**	**Total Biomass (t/ha)**	**Total C (t/ha)**
1	165.2	77.64	42.9	20.16	208.1	97.81
2	201	94.47	52.3	24.58	253.3	119.05
3	141.6	66.55	36.8	17.30	178.4	83.85
4	133.6	62.79	34.7	16.31	168.3	79.10
5	118.1	55.51	30.7	14.43	148.8	69.94
6	132.5	62.28	34.5	16.22	167	78.49
7	93	43.71	24.2	11.37	117.1	55.04
8	246.8	116.00	64.2	30.17	311	146.17
9	13.1	6.16	3.4	1.60	16.5	7.76
10	45.2	21.24	11.7	5.50	56.9	26.74
11	42.1	19.79	10.9	5.12	53	24.91
12	62.3	29.28	16.2	7.61	78.6	36.94
13	23.1	10.86	6	2.82	29.2	13.72
14	41.1	19.32	10.7	5.03	51.7	24.30
15	31.9	14.99	8.3	3.90	40.2	18.89
16	50.3	23.64	13.1	6.16	63.4	29.80
17	33.4	15.70	8.7	4.09	42.1	19.79
18	26	12.22	6.8	3.20	32.7	15.37
19	32.2	15.13	8.4	3.95	40.6	19.08
20	28.1	13.21	7.3	3.43	35.5	16.69
Mean	**83**	**39.02**	**21.6**	**10.15**	**104.6**	**49.17**

Table 6: Total stem number, volume, biomass and carbon stocks of the examined forests

Tabelle 6: Gesamtanzahl der Bäume, Volumen, Biomasse und Kohlenstoffvorräte der untersuchten Wälder

Name of Forest	**Area (ha)**	**Stem number ha^{-1}**	**Total Stem number**	**Volume (m^3/ha)**	**Total Volume (m^3)**	**AGB (t/ha)**	**BGB (t/ha)**	**Biomass (t/ha)**	**Total Biomass (t)**	**AGC (t/ha)**	**BGC (t/ha)**	**C stock (t/ha)**	**Total C Stock**
Garamthun	374.1	1350	505035	102.5	38345.25	148.65	38.65	187.30	70068	69.84	18.142	87.98	32931.9
Chhoi	71.6	870	62292	80.2	5742.32	117.63	30.58	148.22	10612	55.27	14.335	69.607	4987.6
Mohara-Gutta	52.6	650	34190	31.2	1641.12	43.62	11.34	54.97	2891	20.49	5.311	25.803	1358.7
Sanaba	53.4	750	40050	30.5	1628.7	42.74	11.11	53.85	2875.5	2.006	5.217	25.286	1351.4
Dobandi	74.8	880	65824	29.1	2176.68	39.16	10.18	49.34	3690.6	18.37	4.747	23.124	1734.5
Sarandana	70.8	740	52392	20.7	1465.56	28.78	7.48	36.27	2567	13.48	3.478	16.96	1206.4
Total	**697.3**		**759783**		**50999.6**				**92704.1**				**43570.9**

3.4 Carbon Sequestration Potential

The CO_2 equivalent sequestered by these forests was determined by multiplying carbon stock with 3.66. Thus the total amount of CO_2 sequestered by these forests was 159374 t. This is the resulting number of carbon credits as one carbon credit is equal to 1 t CO_2¬. Consequently, if the price of one carbon credit is assumed to be 30 US$ (Nordhaus, 2008), then the total worth of these forests in terms of carbon sequestration is 4781220 US$.

3.5 Testing Spectral Indices

Different vegetation indices were assessed for their correlation with above ground biomass values. There are several bands combinations for Sentinel-2A data (Table 2). Results obtained for different regression models for each index are shown in Table 7. Among these indices NDVI has the highest value of R2 of 0.81, followed by SAVI and DVI with 0.70 and 0.58 respectively. Similarly, applying various regression models (linear, polynomial, power, logarithmic and exponential) the values of R2 change as per data behavior and model assumptions. Landsat-8 imagery indices are summarized in Table 7. Three Landsat-8 indices; NDVI, SAVI and DVI gave low values of R2 as compared to Sentinel-2A indices. However, two Landsat-8 indices (MSAVI and PVI) obtained much higher values of R2 in comparison to Sentinel-2A. Values of R2 of all Landsat-8 indices are tabulated (Table 7). Vafaei et al., (2018) reported that integration of Sentinel-2A with ALOS-2 PALSAR-2 can enhance biomass estimation with greater accuracy. Among these two biomass estimation of Sentinel-2A was more accurate. Adnan, (2017) reported that indices computed from Sentinel-2A have potential to estimate biomass in contrast to vegetation indices of other sensors. Coefficient of determination of NDVI depicted highest changes from 0.62 to 0.81 when the model was switched from linear to polynomial, followed by SAVI and DVI. Other indices MSAVI and PVI have revealed fewer changes while using different models. Scatterplots of all indices and their best models are shown in Figure 4. Whereas, scatterplots of all five indices are in Figure 5. The summary of the linear model for all indices is presented (Table 8). It explains that NDVI obtained the highest value of R^2 (0.71) followed by the SAVI and DVI. Comparative visualization of all indices with Sentinel-2A product is shown in Figure 3. NDVI map was relatively most appropriate to map biomass among other indices.

Table 7: Coefficient of Determination (R^2) of different models for Sentinel-2A and Landsat 8 Products

Tabelle 7: Bestimmtheitsmaß (R^2) von verschiedener Modellen und Vegetationsindices für Sentinel-2A und Landsat-8 Daten

Model	Spectral Indices									
	NDVI		SAVI		DVI		MSAVI		PVI	
	S2A	L8	S2A	L8	S2A	L8	S2A	L8	S2A	L8
Linear	0.62	0.56	0.67	0.55	0.58	0.52	0.04	0.53	0.05	0.52
Power	0.72	0.46	0.70	0.46	0.52	0.46	0.06	0.45	0.09	0.46
Polynomial	0.81	0.64	0.69	0.62	0.58	0.56	0.11	0.60	0.18	0.56
Logarithmic	0.53	0.30	0.64	0.31	0.56	0.34	0.06	0.30	0.08	0.32
Exponential	0.79	0.67	0.68	0.66	0.51	0.59	0.05	0.65	0.06	0.59
Note: S2A= Sentinel-2A, L8 = Landsat-8										

Table 8: Summary Statistics of Linear Model for Sentinel-2A

Tabelle 8: Statische Kennzahlen des linearen Modells für Sentinel-2A

Indices	Equation	R^2	SE	F
NDVI	Y = 450.18x - 153.09	0.62	0.071	26.65
SAVI	Y = 811.35x - 140.98	0.67	0.038	33.75
DVI	Y = 1243.8x - 92.87	0.58	0.026	22.19
MSAVI	Y= -236.57 x + 156.99	0.04	65.22	0.82
PVI	Y = -558.38x + 159.05	0.05	64.89	0.99

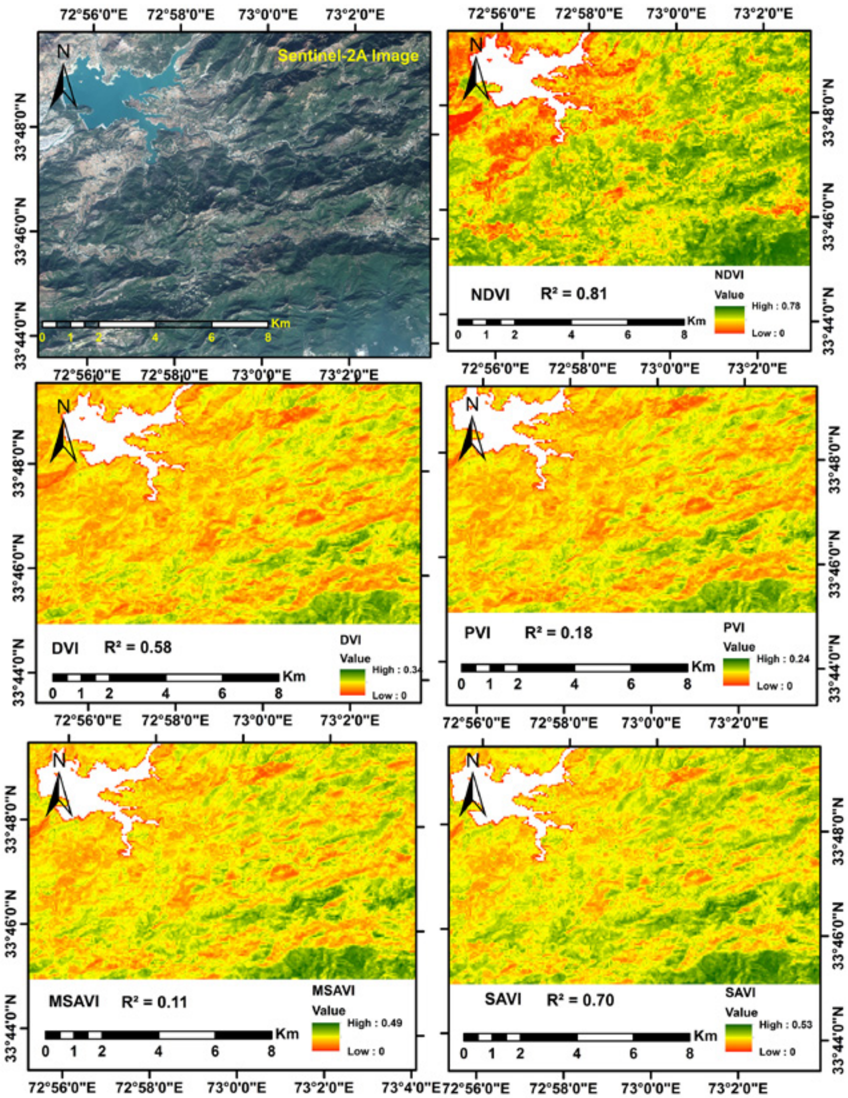

Figure 3: Comparison of Sentinel-2A spectral indices with Sentinel-2A RGB image

Abbildung 3: Vergleich von Sentinel-2A Vegetationsindizes mit Sentinel-2A RGB-Bild

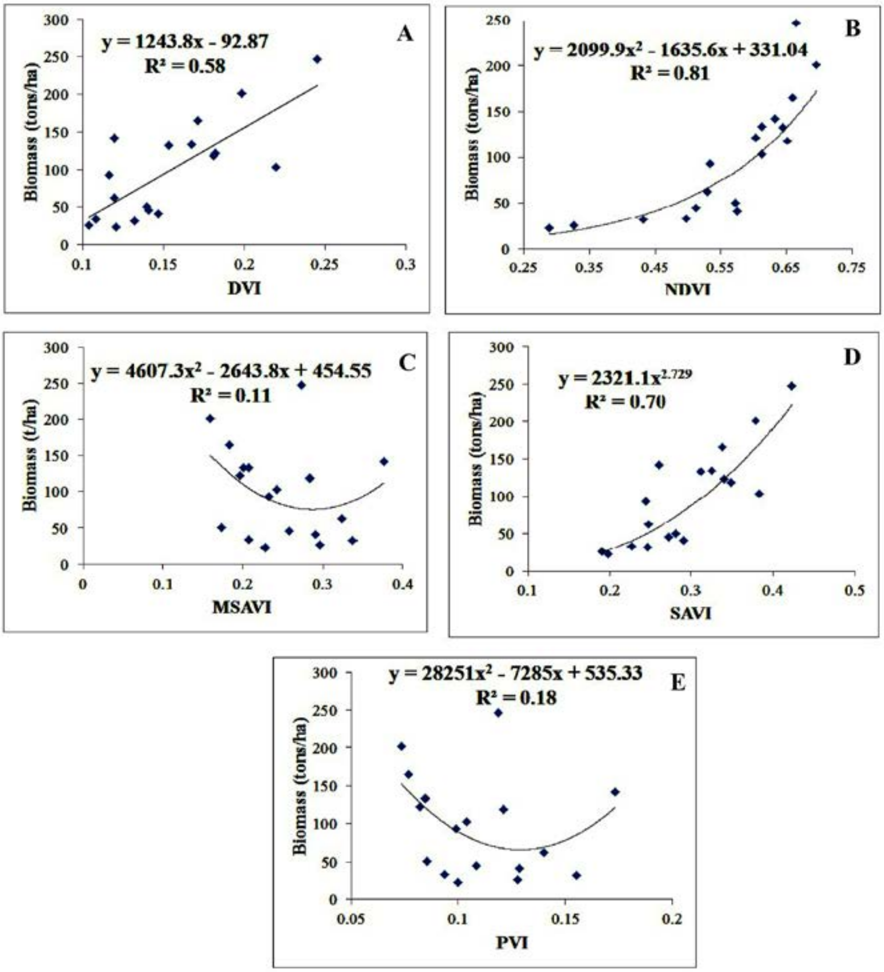

Figure 4: Scatterplots of Sentinel-2A spectral indices and biomass

Abbildung 4: Streudiagramm der Sentinel-2A Vegetationsindizes und Biomasse

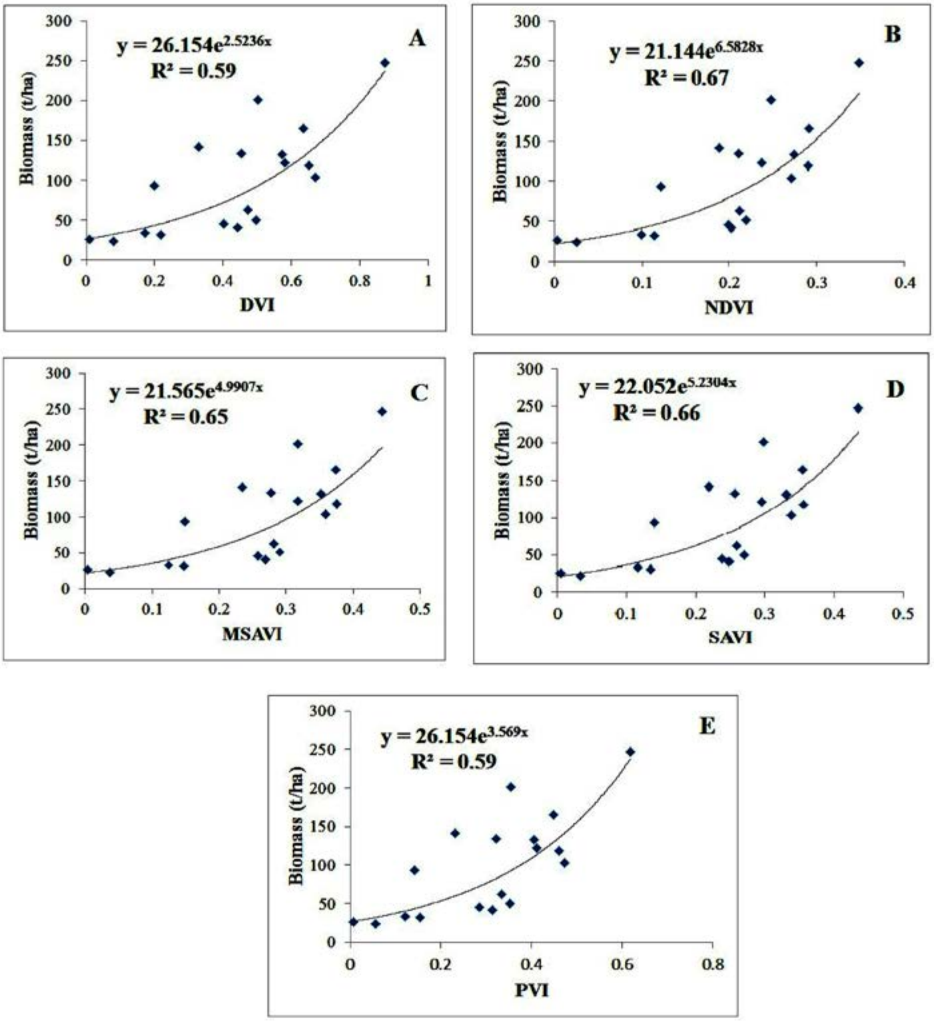

Figure 5: Scatterplots of Landsat-8 spectral indices and biomass

Abbildung 5: Streudiagramm der Landsat-8 Vegetationsindizes und Biomasse

3.6 Mapping of Biomass

Among the various indices, NDVI performed as best predictor to estimate and map biomass of study sites. Therefore, biomass map was produced using raster calculator in ArcGIS 10.3. Linear Model of both Sentinel-2A and Landsat-8 was used to develop biomass and carbon stock maps. Comparison of both maps for Sentinel-2A and Landsat 8 is shown in Figure 6. Moreover, high correlation was shown between predicted and observed biomass with the value of R2 (0.85) and Root Mean Square (RMSE) was 26 t/ha based on NDVI regression equation (linear model) for Sentinel-2A.

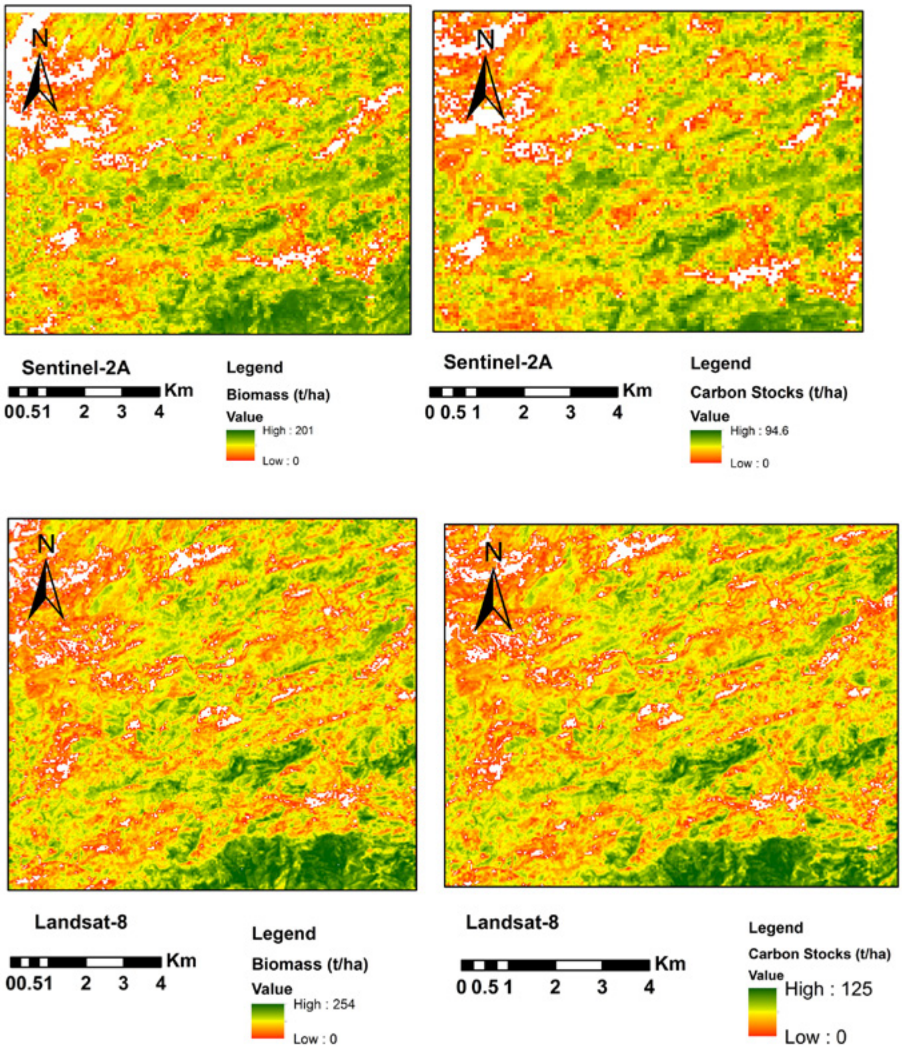

Figure 6: Biomass and Carbon Stocks Map for Sentinel-2A and Landsat-8

Abbildung 6: Biomasse- und Kohlenstoffvorräte für Sentinel-2A und Landsat-8

4. Conclusion

The study suggested that Sentinel-2A product has considerable potential to estimate biomass and map forest areas. The Sentinel-2A product has comparatively large spatial coverage and high resolution to perform efficiently for estimation of biomass than other open source sensors data products. In this study, three indices (NDVI, DVI, SAVI) of Sentinel-2A performed better as compared to indices derived by LANDSAT-8. However, two indices (PVI and MSAVI) had a poor performance. Further researches should be conducted to utilize Sentinel-2A data for deriving various forests attributes to evaluate its role in controlling climate change and to get effective results after its combination with forest inventory data. Such studies have potential applications in integration of remote sensing and forestry inventory for REDD+ readiness and implementation in study area (Chakraborty, 2010). The global data availability of Sentinel-2 and Landsat-8 data products shows great potential for regional and global scales biomass and carbon mapping and monitoring and can be used for European forests as well (Neumann et al., 2016).

The study concluded that scrub forest show great potential for carbon sequestration and storage. Thus, it can be considered vital in climate change mitigation in Pakistan. Khanpur sub-tropical scrub forest is of paramount significance as it stores suitable amount of carbon, and seemed to be unobstructed from any sort of anthropogenic influence. Thus study measured the worth of these forests in terms of carbon sequestration, showing that there is a great potential of CO_2 sequestration and evaluated their environmental role in combating climate change. Hence, it is concluded that by raising and protecting these forests, a large amount of carbon can be sequestered in future. Therefore, supplementary carbon credits can be earned through carbon trading under REDD+ forest management (Reducing Emissions from Deforestation and forest Degradation).

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